

## Solution 1: Lasso Regularization

(a) First of all, we will use the fact that  $\mathbf{X}$  has orthonormal columns to show that:

$$\begin{aligned}\hat{\boldsymbol{\theta}} &= \left( \underbrace{\mathbf{X}^T \mathbf{X}}_I \right)^{-1} \mathbf{X}^T \mathbf{y} \\ \hat{\boldsymbol{\theta}} &= \mathbf{X}^T \mathbf{y}\end{aligned}\tag{1}$$

We will now use the result of eq. 1 to show that:

$$\begin{aligned}\arg \min_{\boldsymbol{\theta}} \mathcal{R}_{\text{reg}}(\boldsymbol{\theta}) &= \arg \min_{\boldsymbol{\theta}} \frac{1}{2} \sum_{i=1}^n \left( y^{(i)} - \boldsymbol{\theta}^T \mathbf{X}^{(i)} \right)^2 + \lambda \sum_{i=1}^p |\theta_i| \\ &= \arg \min_{\boldsymbol{\theta}} \frac{1}{2} \|\mathbf{y} - \mathbf{X}\boldsymbol{\theta}\|_2^2 + \lambda \|\boldsymbol{\theta}\|_1 \\ &= \arg \min_{\boldsymbol{\theta}} \frac{1}{2} (\mathbf{y} - \mathbf{X}\boldsymbol{\theta})^T (\mathbf{y} - \mathbf{X}\boldsymbol{\theta}) + \lambda \|\boldsymbol{\theta}\|_1 \\ &= \arg \min_{\boldsymbol{\theta}} \frac{1}{2} \left( \underbrace{\mathbf{y}^T \mathbf{y}}_{\text{indep. of } \boldsymbol{\theta}} - 2 \underbrace{\mathbf{y}^T \mathbf{X} \boldsymbol{\theta}}_{\boldsymbol{\theta}^T} + \boldsymbol{\theta}^T \underbrace{\mathbf{X}^T \mathbf{X} \boldsymbol{\theta}}_I \right) + \lambda \|\boldsymbol{\theta}\|_1 \\ &= \arg \min_{\boldsymbol{\theta}} -\hat{\boldsymbol{\theta}}^T \boldsymbol{\theta} + \frac{\boldsymbol{\theta}^T \boldsymbol{\theta}}{2} + \lambda \|\boldsymbol{\theta}\|_1 \\ &= \arg \min_{\boldsymbol{\theta}} \sum_{i=1}^p -\hat{\theta}_i \theta_i + \frac{\theta_i^2}{2} + \lambda |\theta_i|.\end{aligned}\tag{2}$$

(b) The advantage of this representation if we are interested in finding  $\boldsymbol{\theta}$  is that we can optimize each  $g_i(\theta_i)$  separately to get optimal entries for  $\theta_1, \dots, \theta_p$ .

(c) Let's use the hint and compare  $g_i(\theta_i)$  with  $g_i(-\theta_i)$ , for the case where  $\theta_i > 0$  :

$$\begin{aligned}g_i(\theta_i) &= -\hat{\theta}_i \theta_i + \frac{\theta_i^2}{2} + \lambda |\theta_i| \\ g_i(-\theta_i) &= +\hat{\theta}_i \theta_i + \frac{(-\theta_i)^2}{2} + \lambda |\theta_i|\end{aligned}\tag{3}$$

We also know that non-positive  $\theta_i$  have always a greater or equal value for  $g_i(\theta_i)$  than their positive counterpart:

$$\theta_i > 0 \longrightarrow g_i(\theta_i) \leq g_i(-\theta_i)\tag{4}$$

The second and third term of both equations in eq. 3 are equivalent, so we can ignore them. Accordingly, to comply with the condition from eq. 4, the minimizer  $\theta_i^*$  must be non-negative.

$$-\hat{\theta}_i \theta_i \leq \hat{\theta}_i \theta_i \longrightarrow \theta_i^* \geq 0\tag{5}$$

(d) To calculate the minimizer  $\theta_i^*$ , we will derive with respect to the parameter and set the derivative to zero:

$$\begin{aligned}
\frac{\partial g_i(\theta_i)}{\partial \theta_i} &= -\hat{\theta}_i + \theta_i + \underbrace{\lambda}_{\theta_i > 0} \\
&= -\hat{\theta}_i + \theta_i + \lambda \stackrel{!}{=} 0 \longrightarrow \theta_i = \underbrace{\hat{\theta}_i - \lambda}_{\geq 0} \\
\theta_i^* &= \underbrace{\hat{\theta}_i - \lambda}_{\geq 0} \\
&= \max(0, \hat{\theta}_i - \lambda)
\end{aligned} \tag{6}$$

(e) Let's use the hint again and compare  $g_i(\theta_i)$  with  $g_i(-\theta_i)$ , for the case where  $\theta_i < 0$  :

$$\begin{aligned}
g_i(\theta_i) &= -\hat{\theta}_i \theta_i + \frac{\theta_i^2}{2} + \lambda |\theta_i| \\
g_i(-\theta_i) &= +\hat{\theta}_i \theta_i + \frac{(-\theta_i)^2}{2} + \lambda |\theta_i|
\end{aligned} \tag{7}$$

$$\theta_i < 0 \longrightarrow g_i(\theta_i) \geq g_i(-\theta_i) \tag{8}$$

The second and third term in both equations of 7 are equivalent. Using the condition from eq. 8, we can conclude that the minimizer  $\theta_i^*$  must be non-positive.

$$-\hat{\theta}_i \theta_i \geq \hat{\theta}_i \theta_i \longrightarrow \theta_i^* \leq 0 \tag{9}$$

(f) Calculating the derivative again and setting it to zero, we get:

$$\begin{aligned}
\frac{\partial g_i(\theta_i)}{\partial \theta_i} &= -\hat{\theta}_i + \theta_i \underbrace{-\lambda}_{\theta_i < 0} \stackrel{!}{=} 0 \longrightarrow \theta_i = \underbrace{\hat{\theta}_i + \lambda}_{\leq 0} \\
\theta_i^* &= \underbrace{\hat{\theta}_i + \lambda}_{\leq 0} \\
&= \min(0, \hat{\theta}_i + \lambda)
\end{aligned} \tag{10}$$

(g)

$$\left\{ \begin{aligned} \theta_i > 0 &\longrightarrow \theta_i^* = \underbrace{\text{sign}(\hat{\theta}_i)}_1 \cdot \max(0, \underbrace{\hat{\theta}_i}_{=|\hat{\theta}_i|} - \lambda) \\ \theta_i \leq 0 &\longrightarrow \theta_i^* = \min(0, \hat{\theta}_i + \lambda) = \underbrace{-1}_{\text{sign}(\hat{\theta}_i)} \cdot \max(0, \underbrace{-\hat{\theta}_i}_{=|\hat{\theta}_i|} - \lambda) \end{aligned} \right. \tag{11}$$

By transforming the min function from 10 to a max function, we can combine the two cases in only one expression:

$$\theta_i^* = \text{sign}(\hat{\theta}_i) \max(|\hat{\theta}_i| - \lambda, 0) \tag{12}$$